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A review of operations research (OR) methods applicable to wildfire management

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Abstract

Across the globe wildfire-related destruction appears to be worsening despite increased fire suppression expenditure. At the same time, wildfire management is becoming increasingly complicated due to factors such as an expanding wildland-urban interface, inter-agency resource sharing and the recognition of the beneficial effects of fire on ecosystems. OR is the use of analytical techniques such as mathematical modelling to analyse interactions between people, resources and the environment to aid decision-making in complex systems. Fire managers operate in a highly challenging decision environment characterised by complexity, multiple conflicting objectives and uncertainty. We assert that some of these difficulties can be resolved with the use of OR methods. We present a range of OR methods and discuss their applicability to wildfire management with illustrative examples drawn from the wildfire and disaster OR literature.

Additional keywords: bushfire, forest fire, wildland fire, operational research, decision-making, management science

Summary for Table of Contents

Wildfire managers operate in a highly challenging decision environment characterised by complexity, multiple conflicting objectives and uncertainty. Operations research (OR) is a discipline that uses analytical techniques to aid

decision making in complex systems. This paper discusses a range of OR methods available to assist wildfire managers with illustrative examples drawn from the wildfire and disaster OR literature.

Introduction

The February 2009 bushfires in Victoria, Australia provided a stark reminder of the destructive potential of wildfire. The fires resulted in 173 fatalities and damage to property, infrastructure and the natural environment with an estimated total cost of over A$4 billion (Teague et al. 2010). Globally, wildfire-related destruction is a problem that appears to be worsening. In the Mediterranean basin a sharp increase in wildfire events has been observed over the past several decades despite increased investment in prevention and suppression (Carmel et al. 2009; Pappis and Rachaniotis 2010). Increased wildfire activity has also been observed in the United States (Westerling et al. 2006) and Canada (Podur et al. 2002). This upward trend appears set to continue due to rising temperatures and changed weather conditions associated with climate change (Wotton et al. 2003; Westerling et al. 2006). As suppression expenditures continue to rise, governments seek wildfire management approaches that are economically efficient and that take into account both market and non-market benefits (Venn and Calkin 2011).

Wildfire managers operate in a difficult decision environment. They are faced with limited time, constrained resources, extreme uncertainty and multiple objectives that may conflict (Martell et al. 1998). In recent years, wildfire management has become increasingly complex with the advent of inter-agency resource sharing arrangements and the recognition of the beneficial effects of fire on ecosystems (Martell 2011). Operations Research (OR) is a discipline that is uniquely placed to assist managers operating in this challenging environment. OR is the use of analytical techniques such as mathematical modelling to analyse complex interactions between people, resources and the environment to aid decision-making and the design and operation of systems (Altay and Green 2006). Wildfire managers have access to a proliferation of data from a variety of sources including geospatial databases and fire behaviour and climatology models. OR methods can provide a framework to help wildfire managers make sense of this information and use it to guide decision-making.

There is a large body of disaster management OR work relating to non-routine emergency events such as: earthquakes, floods and hurricanes (Altay and Green 2006). There is also a substantive literature on the application of OR to wildfire-specific management problems. Martell (1982) conducted a comprehensive review of wildfire OR work from 1961 to 1981 with elements of this review updated in 1998 (Martell et al. 1998), as such this paper will focus on post-1998 wildfire OR work. The remainder of the paper is structured as follows. A range of OR methods will be discussed in terms of their ability to address some of the defining challenges of wildfire management, namely: complexity, multiple conflicting objectives and uncertainty. Illustrative examples and case studies drawn from the wildfire and disaster OR literature will be presented for each of the OR methods discussed.

Methods for handling complexity

Mathematical programming

Wildfire managers are often faced with complex problems consisting of a large number of inter-related decisions together with resourcing and other operational constraints. Mathematical programming (MP) is a field of OR that can assist with such problems. MP methods are concerned with the optimization, that is maximization or minimization, of some explicit and quantifiable objective (Williams 1990). In an MP model this objective is defined as a mathematical function of the decision variables in the form of an ‘objective function’ and is optimized subject to a series of related constraints (Hillier and Lieberman 2005). Several categories of MP: linear programming (LP), integer programming (IP), nonlinear programming (NLP) and dynamic programming (DP) are described in further detail below together with examples from the wildfire and disaster OR literature.

Linear programming (LP) can be used when a problem’s objective function and constraints can be formulated as a linear combination of the decision variables (Ragsdale 2008). Hof et al. (2000) developed a timing-oriented LP model for the spatial allocation of suppression effort for an existing fire. Their model’s objective was to delay the ignition of “protection areas” such as population centres. In an extension of this work Hof and Omi (2003) described the application of a similar timing-oriented LP model to a fuel management scheduling problem. In their model, spatial application of fuel-reduction treatments were determined so as to mitigate the effects of a particular “target fire” with a known origin and spread behaviour. When a LP model is solved a “shadow price” is generated for each constraint as a standard model output. Shadow prices can be interpreted as the marginal effect that tightening or relaxing a constraint has on the objective value obtained (Williams 1990). Armstrong and Cumming (2003) used shadow prices obtained from a timber-harvesting LP model to estimate the potential cost of land based changes due to wildfire. Spatially explicit values-at-risk information like this can be useful for fuel treatment and suppression preparedness planning.

Integer programming (IP) models feature inputs or outputs that are required to take on discrete whole number values. IP can be useful for modelling problems that feature: indivisible resources, “yes or no” decisions or logical connections such as “if” and “then” (Wolsey 1998). IP methods have been applied to a range of wildfire management problems. The maximal covering location model (MCLM) is a classic IP model that has been used extensively in emergency service deployment (Church and ReVelle 1974). Dimopoulou and Giannikos (2001; 2004) described the use of an MCLM model for suppression resource deployment as part of a decision support system that also included a simulation module and a GIS interface. Kirsch and Rideout (2005) presented an IP model for initial attack preparedness planning. Their model deployed initial attack resources across a user-defined set of fires with the objective being to maximise the weighted area protected (WAP) for a given level of budget funding, with weights assigned based on protection priorities. Donovan (2006) presented a model for determining the optimal mix of agency and contract fire crews to minimise costs and satisfy demand across a fire season. A multi-period transportation formulation was used with the fire season modelled as a series of discrete time periods with differing levels of demand. This approach resulted in reduced computational complexity for this type of problem as compared to a standard IP formulation. Donovan and Rideout (2003) described an IP model to determine the optimal mix of fire-fighting resources to dispatch to a given fire to achieve containment with minimal resultant costs and damages. Wei et al. (2008) formulated an IP model for optimal allocation of fuel treatment across a landscape based on spatially explicit ignition risk, fire spread probability, fire intensity levels and values-at-risk. Higgins et al. (2011) used an IP approach to develop a seasonal resource allocation model for planning fuel reduction burning on public lands in Victoria, Australia.

Nonlinear programming (NLP) methods are used when a problem features a nonlinear objective function or nonlinear constraints. The probability of containing a wildfire and the suppression time required to do so are nonlinear functions of fire size at the start of initial attack. This means small delays in dispatch of initial attack resources can result in dramatic fire loss increases (MacLellan and Martell 1996). Rachaniotis and Pappis sought to incorporate this element of fire behaviour in an NLP model via the use of the “deteriorating jobs” concept. Their model tackled the problem of scheduling a single fire-fighting resource when there are several existing fires to be controlled (Rachaniotis and Pappis 2006; Pappis and Rachaniotis 2010; Rachaniotis and Pappis 2011). The model was subsequently extended to allow scheduling of multiple fire-fighting resources (Pappis and Rachaniotis 2009). Minciardi et al. (2009) formulated two related NLP models, one for deployment of wildfire suppression resources in the pre-operational phase and the other for dispatch of resources to fires in the operational phase.

Dynamic programming (DP) is an optimisation method that is particularly useful when sequences of interrelated decisions need to be made. In deterministic DP the state of the system at the next stage is completely determined by the current system state and the policy decision made (Hillier and Lieberman 2005). Wiitala (1999) used a DP model to determine the most efficient mix of available initial attack resources to dispatch to a fire.

Problem structuring methods

Traditional 'OR' methods such as mathematical programming are suited to well-structured problems that can be clearly formulated in terms of performance measures, constraints and relations between action and consequence. However, many wildfire and disaster management problems lack structure and are typified by multiple perspectives, disagreement amongst experts and the presence of intangibles and uncertainties. Problem structuring methods (PSM) are a suite of techniques that can assist in resolving some of these difficulties. Compared to traditional 'hard' OR methods PSM typically employ rudimentary mathematical or statistical techniques (Mingers and Rosenhead 2004). Two PSM methods, decision conferencing and expert judgement elicitation, are discussed in further detail below.

Decision conferencing can be an effective method for assisting with longer-term collaborative decision making. A decision conference is typically a two-day event that brings together decision makers from various organisations to discuss issues and work out a way forward. A facilitator is present to keep the discussion focused. An analyst is also present to build a series of analytical decision models with a view to developing a shared understanding of the problem (French 1996). A series of decision conferences were held in the USSR following the 1986 Chernobyl nuclear accident. The aim was to identify the major factors influencing decision-making on relocation and other long term protective measures. The decision conferences helped develop a common understanding amongst participants including government ministers, policy-makers and scientists and successfully identified a number of key medical, socio-economic and political factors influencing protective measures undertaken (French et al. 1992). Decision conferencing could be similarly used following major wildfires to facilitate dialogue between stakeholders and aid recovery-phase planning.

Expert judgement elicitation (EJE) is the use of structured methods to elicit expert opinions in a planned, formal manner that attempts to minimize bias. EJE typically involves interviewing or surveying "subject experts" and then analysing their answers together with information about their background and experience. EJE methods can provide an understanding of the degree of and reasons for consensus or disagreement amongst experts and can be useful in facilitating learning and dialogue (Gregory et al. 2006). Furthermore, EJE studies are often a cost-effective and practical means of obtaining valuable information. In the wildfire context, EJE methods have been used to estimate fire containment probabilities and fire-line construction rates. In these instances, alternate methods such as observation of actual or experimental fires are often deemed to be too expensive, time-consuming and dangerous (Hirsch et al. 1998). In one of the earliest applications of EJE methods to wildfire management subjective probability assessments of daily forest fire occurrence were derived using information elicited from experienced fire managers in Ontario (Cunningham and Martell 1976). Hirsch et al. (1998) used an EJE approach to model the relationship between fire size, fire intensity and probability-of-containment by a 5-7 person initial attack crew. In their study they interviewed crew leaders from four Canadian forest fire agencies and elicited probability-of-containment estimates for various fire scenarios (Hirsch et al. 1998). Gilless and Fried (2000) surveyed California fire-fighters and used their responses to estimate probability distributions for fire-line construction rates for different fire-fighting resources under a range of conditions. These fire-line construction rate distributions were subsequently incorporated into the CFES2 simulation model used for initial attack planning in California. Similarly, Hirsch et al. (2004) interviewed crew leaders in Ontario and developed probability distributions for production rates of three and four person initial attack crews for a range of fuel types and fire intensities. Rideout et al. (2008) used EJE methods in their Marginal Attribute Rate of Substitution (MARS) approach to assessing values-at-risk for initial attack planning.

System dynamics

In complex systems, components can interact with one another via a web of feedback loops meaning a small change to input parameters can produce a drastic change to the whole system (Anderson 1999). These feedback effects can be modelled using system dynamics (SD). Unlike many traditional ‘hard’ OR approaches that are static and linear in character, SD can accept the nonlinearity and feedback loop structures of real world social and physical systems. Whilst SD uses a ‘soft’ PSM-like approach for information elicitation and problem structuring, it includes two additional ‘hard’ steps: model definition using rate and level equations and the running of model simulations. An SD model initially serves to demonstrate how the problem under consideration is being generated in the real world, it is subsequently used to test alternative policies and structures (Forrester 1994). Hoard et al. (2005) discussed the application of SD methods to disaster preparedness planning in rural areas with a focus on hospital surge capacity for a variety of disaster types. A similar SD approach could be used in wildfire preparedness planning to explore surge capacity considerations in suppression resource deployment and rostering of fire-fighting personnel.

Hyper-projects

Wildfire incident controllers are dealing with a problem that is emergent in nature. They are faced with a 'moving target' or a dynamic set of changing circumstances. The incident trajectory is influenced by actions taken such as fire suppression and external forces such as weather (Faraj and Xiao 2006). Simpson (2006) defined a class of project, the 'hyper-project', that captures these emergent characteristics. Hyper-projects are characterised by the presence of a dynamic, external 'pacing function' and a set of defined tasks and resource requirements that interact with this pacing function. Time pressure is an inherent feature of hyper-projects, with tasks measured in minutes or hours. Simpson (2006) used the hyper-project construct to model response to a residential structure fire, a similar approach could be used to model real-time wildfire suppression decision-making. In such a model various suppression resources would be dispatched and tactical fire-fighting decisions made relative to an external pacing function, which in this case would be the growth and lifecycle of the uncontained wildfire. The hyper-project approach can capture threshold effects, a key feature of complex biophysical systems. Thresholds are breakpoints that occur in systems with multiple stable states where crossing a threshold results in a shift from one state to another (Berkes 2007). An example being when a wildfire crosses the 4000 kW/m threshold it can be said to have changed state from a controllable fire to a spot generating fire (Gill 2005) thus requiring a different suppression response. The hyper-project provides a framework for responding to state changes via the execution of a flexible set of tasks that vary in a pre-defined manner relative to the pacing function.

Methods for handling multiple conflicting objectives

Multi-objective optimization

Wildfire management involves various agencies and groups with different priorities and objectives including: reduction of impacts on public safety, private property and ecosystem processes as well as cost minimisation (Martell 2007). Instances will often arise where multiple objectives conflict with one another, for example frequent planned burning can provide additional protection to built assets but may have a negative impact on biodiversity in some ecosystems (Driscoll et al. 2010). Where multiple objectives can be expressed in terms of market values they can be aggregated into a single cost minimization objective. However wildfire managers are required to consider potential impacts on non-market values such as: ecosystem health, conservation of flora and fauna, air quality, water quality, recreational opportunities and cultural heritage (Venn and Calkin 2011). In many cases ascribing a monetary value to these items would be an expensive, time-consuming and uncertain exercise. This lack of a common currency makes it difficult to evaluate and compare the outcomes of decisions or strategies. Multi-objective optimization (MO) is a technique that is suited to these types of problems. MO models are formulated with more than one objective function to find a set of Pareto optimal solutions. A solution is Pareto optimal if none of the objectives can be improved without making another objective worse. Decision-makers can assess alternatives from this set of Pareto optimal solutions by examining trade-offs amongst the various objective values. This explicit identification and structured exploration of trade-offs provides a level of transparency in the decision process (Gregory et al. 2006). Lehmkuhl et al. (2007) described FUELSOLVE a prototype decision support system that incorporates MO modelling into fuel management decision-making to consider both ecological and cost objectives. Kennedy et al. (2008) demonstrated the use of the FUELSOLVE MO model with a fuel treatment case study with trade-offs assessed between protection of endangered species habitat, preservation of old growth forest reserves and minimization of area treated.

Goal Programming (GP) is a branch of multi-objective optimization in which each of the multiple objectives takes the form of a goal. Goals are formulated as ‘soft constraints’ each with a target value it is desirable to satisfy. A penalty function is then specified that seeks to minimise deviations from this set of target values. Adjustments to the penalty function parameters allows the exploration of trade-offs between objectives (Ragsdale 2008). Calkin et al. (2005) used a GP approach to analyse trade-offs between fire threat reduction and habitat preservation in silvicultural treatment scheduling. A goal programming module is currently under development as part of the United States Fire Program Analysis (FPA) project (Kumar et al. 2010). The FPA project has been undertaken by the US Forest Service and other federal land management agencies in an attempt to develop a wildfire management planning and budgeting decision-support tool that will incorporate a full range of both market and non-market objectives (Venn and Calkin 2011).

Methods for handling uncertainty

Simulation

Wildfire managers are required to make difficult decisions in conditions of uncertainty. Simulation is arguably the most robust and easily applied method for consideration of uncertainty in decision support systems (Mowrer 2000). Simulation is an approach used to model real-life stochastic systems that evolve probabilistically over time. The real-life system's performance is imitated by using probability distributions to generate various events that occur in the system (Hillier and Lieberman 2005). Prior to implementation, simulation models require validation to ensure they realistically represent the system being analysed and that the results they provide are reliable (Winston 1994). Simulation models feature in a number of decision support systems used by wildfire agencies for strategic planning purposes. The California Fire Economics Simulator version 2 (CFES2) is a stochastic simulation model that simulates fire occurrence and suppression on a daily basis. Simulation of many years of "data" makes it possible to undertake "what if" analysis for changes to organisational components such as: resource stationing, dispatch rules and staff schedules (Fried et al. 2006). The Level of Protection Analysis System (LEOPARDS) is underpinned by a simulation model that is spatially conscious and incorporates temporal queuing conflicts. LEOPARDS can model daily fire suppression activities and is used in Ontario to assess initial attack performance under a range of policy and budget conditions (McAlpine and Hirsch 1999). LEOPARDS has evolved from an initial attack simulation model that was developed in the early 1980s by Martell et al. (1984). The USDA Forest Service's National Fire Management Analysis System (NFMAS) Interagency Initial Attack Assessment (IIAA) is a simulation model that has been used in the past to test alternative initial attack organisations and strategies at various budget levels with a view to determining the Most Efficient Level (MEL) of funding (Lundgren 1999). Manipulation of simulation models can provide valuable insights into a problem, however the primary shortcoming of this approach is that it is only possible to find "the best" management alternative from those investigated. For large problems with many management alternatives it is unlikely that a near-optimal solution can be found in this manner. For this reason, mathematical programming (MP) methods that systemically explore the solution-space can add significant value to complex wildfire management problems (Hof and Haight 2007).

Stochastic programming

Stochastic programming (SP) is a method that combines mathematical programming methods with probability techniques to provide a constructive approach to tackling optimization problems that feature uncertain data. SP can be used when there are uncertain model parameters with probability distributions that are known or can be estimated (Kall and Wallace 1994). These parameter distributions can be either continuous or described by discrete scenarios and in some cases are generated using simulation techniques. The most common SP objective is optimization of the mean outcome or expected value of the system. An alternate formulation incorporating decision maker risk preferences is the optimization of a weighted sum of expected value and variance (Snyder 2006). SP models generate solutions that are less sensitive to data uncertainty than deterministic MP models, however large SP models can prove difficult to solve.

One of the earliest uses of SP methods in forest fire management was Boychuk and Martell's (1996) multi-stage model for forest-level timber management that considered uncertain losses that could result from fires. A common SP formulation is the two-stage model with recourse. In such models, a first-stage decision is made after which a random event occurs, a recourse decision can then be made in the second-stage that compensates for any undesirable effects. Hu and Ntaimo (2009) modelled the wildfire initial attack dispatch problem as a two-stage SP model with recourse. In their model the first stage decisions related to dispatch of suppression resources to reported wildfires, with recourse decisions made on fire-fighting tactics in the second stage. Stochastic parameters in the model included: fire growth scenarios, fire-line production rates, arrival times to fires and suppression resource operating costs. Ntaimo (2010) described an alternate application of a two-stage SP approach with deployment of suppression resources to bases in the first-stage and dispatch of resources to wildfires in the second stage. Two-stage SP models have been applied to a range of disaster management problems including: transportation of first-aid commodities on a disaster effected road network (Barbarosoglu and Arda 2004), pre-positioning of emergency supplies in a hurricane-threatened region (Rawls and Turnquist 2010) and locating storehouses and developing transportation plans for flood-relief logistics (Chang et al. 2007).

Probabilistic SP approaches, such as chance-constrained programming, require the probability of a constraint holding to be above a specified threshold (Snyder 2006). Bevers (2007) demonstrated the use of chance-constrained programming for a fire organisation budgeting problem. In his model formulation the probability of total fire costs exceeding the budget was required to be less than a specified risk level.

Stochastic dynamic programming (SDP) is a method used for problems with sequential decisions that are subject to uncertainty. SDP differs from deterministic DP in that state-to-state system transitions are governed by probability distributions (Hillier and Lieberman 2005). Konoshima et al. (2008; 2010) demonstrated the use of an SDP approach for determining optimal spatial patterns of fuel treatment and timber harvesting in a theoretical landscape subject to fire risk. Spring and Kennedy (2005) developed an SDP model with decisions made at the beginning of each stage as to which stands of trees are harvested and what level of fire protection is applied.

Robust optimization

Like stochastic programming (SP), robust optimization (RO) provides a constructive approach to solving optimization problems that feature uncertain data (Vladimirou and Zenios 1997). However RO differs from SP in that probability distributions of uncertain parameters are not required. All that needs to be known about the uncertain parameters is that they belong to some ‘uncertainty set” which may be described as either a continuous interval or as set of discrete scenarios (Ben-Tal and Nemirovski 2002). RO models are a great deal less sensitive to data perturbations than deterministic MP methods but substantially more difficult to solve. RO models can be formulated in a number of ways. The Minimax formulation seeks to minimise the maximum cost or damage across all possible scenarios. This is a highly conservative approach that provides costly solutions that cater for worst-case outcomes (Snyder 2006). Unless a model has significant built-in redundancies a solution is unlikely to remain both feasible and optimal across all scenarios (Vladimirou and Zenios 1997). Model and solution robustness approaches seek to balance optimality and feasibility based on the decision maker’s degree of risk aversion. Restricted scenario approaches minimise the maximum cost or damage across a restricted ‘reliability set’ of scenarios. This reliability set is specified by the decision maker based on risk preferences (Snyder 2006). Haight and Fried (2007) presented a scenario-optimization IP model for suppression resource deployment based on the classical maximal covering model (MCLM). Their formulation included a binary “standard response” variable that served as a proxy for fire-line construction. The model’s objective was to minimize the number of fires not receiving a “standard response” across a defined set of scenarios. Mercer et al.(2008) modified Haight and Fried’s standard-response model to incorporate the effects of fuel treatment. Other problems with relevance to wildfire and disaster management that RO methods have been applied to include evacuation transportation planning (Yao et al. 2009) and facility location under uncertainty (Snyder 2006).

Fuzzy models

Stochastic programming and robust optimization methods are appropriate for problems where uncertainty is mostly due to randomness, however uncertainty is sometimes due to other factors such as imprecision and ambiguity (Verderame et al. 2010). Fuzzy set theory is an approach that can tackle problems that feature fuzzy predicates such as ‘small’ or ‘safe’, fuzzy quantifiers such as ‘most’ or ‘often’, and fuzzy probabilities such as ‘likely’ or ‘unlikely’ (Smithson 1991). In classical set theory membership of a set is assessed in binary terms, that is an element either belongs to a set or it doesn’t. In fuzzy set theory ‘degrees of membership’ ranging from 0 to 1 are permitted based on a fuzzy membership function (Dubois and Prade 1988). Models based on fuzzy set theory have been used to classify areas into risk-zones for both fire prevention planning (Iliadis et al. 2002), (Iliadis et al. 2002b), (Iliadis 2005), (Iliadis and Spartalis 2005), (Kaloudis et al. 2005), (Kaloudis et al. 2008), (Tsataltzinos et al. 2009), (Iliadis et al. 2010) and disaster relief purposes (Sheu 2007), (Tan et al. 2009), (Sheu 2010).

Conclusion

In this paper we have presented a range of OR methods and discussed their ability to address some of the major challenges of wildfire management including: complexity, multiple conflicting objectives and uncertainty. Many of these OR methods are complimentary and can be used in conjunction with one another. Problem structuring methods (PSM) can be used to elicit objectives and opinions and to help develop a common understanding. Simulation and system dynamics (SD) methods can be used to model the dynamics of complex systems to gain insights into the problem structure and possible management prescriptions through the use of "what-if" analysis. Whilst optimization methods such as mathematical programming (MP) can be used to explore the decision space and seek good solutions from the many alternatives.

As more frequent and destructive wildfire events threaten lives and homes in an expanding wildland-urban interface, now more than ever we need to apply best practice analytical methods to assist wildfire managers in assessing alternatives and making decisions. However, there appears to be a large and growing gap between the decision support needs of fire managers and the decision support tools currently available (Martell 2011).We have demonstrated with the use of examples from the literature the role OR techniques can play in bridging this gap. The Victorian Bushfires Royal Commission investigated the catastrophic 2009 bushfires and made a series of recommendations aimed at reducing the risk and impacts of fire and minimising fire-related loss of life (Teague et al. 2010). Of the 67 recommendations made, fifteen could be addressed with the use OR methods, including: consideration of multiple objectives in fuel treatment planning and pre-emptive risk-based deployment of aerial resources.

The many wildfire OR examples discussed in this paper range from those that are largely theoretical in nature to those that have been successfully implemented, such as the LEOPARDS model (McAlpine and Hirsch 1999). As OR formulation methods and algorithms continue to improve and greater computing power become available, it will be possible to tackle increasingly complex wildfire problems using OR methods. However in closing, it is apt to recall Martell's (1982) reminder that OR specialists can develop decision-making aids that will enhance but not replace the experience and intuition of wildfire managers, and that the successful application of OR methods will require the OR analyst to work closely with wildfire agency personnel.

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